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Classification of Electromyogram Using Recurrence Quantification Analysis

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Abstract

Clinical analysis of the electromyogram is a powerful tool for diagnosis of neuromuscular diseases. Therefore, the classification of electromyogram signals has attracted much attention over the years. Several classification methods based on techniques such as neuro-fuzzy systems, wavelet coefficients, and artificial neural networks have been investigated for electromyogram signal classification. However, many of these time series analysis methods are not highly successful in classification of electromyography signals due to their complexity and non-stationarity. In this paper, we introduce a novel approach for the diagnosis of neuromuscular disorders using recurrence quantification analysis and support vector machines.

Electromyogram signals are transformed into recurrence plots and a set of statistical features are extracted using recurrence quantification analysis. Support vector machine employing radial basis functions is used for classifying the normal and abnormal of neuromuscular disorders. Examining the acoustic patterns in electromyogram, we classify the signals into one of the three categories: healthy, neuropathy, and myopathy. The results show that the proposed method classifies these signals with 98.28% accuracy; it is a significantly better accuracy than what has been reported in the literature thus far. The accurate results indicate that proposed diagnosis method of neuromuscular disorders is very effective.

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Keywords: Classification; Dynamical System; Electromyogram; Recurrence Quantification Analysis

1. Introduction

There are more than 100 neuromuscular disorders that affect the brain, spinal cord, nerves, and muscles [1]. Neuromuscular disorders are related to pathological changes in the structure of motor units and can be divided into muscular (myopathy) and neuronal disorders (neuropathy). Myopathy is neuromuscular disorders in which the primary symptom is muscle weakness due to dysfunction of muscle fibres [1]. Neuropathy describes damage to the peripheral nervous system which transmits information from the brain and spinal cord to every other part of the body. Myopathy is neuromuscular disorders in which the primary symptom is muscle weakness due to dysfunction of muscle fibres [1].

Motor unit morphology can be studied by recording its electrical activity which is electromyogram (EMG). In clinical EMG, motor unit potential (MUPs) are recorded using a needle electrode at slight voluntary contraction [2].

A MUP reflects the electrical activity of a single anatomical motor unit. Moreover, they are used to detect and describe different neuromuscular diseases. Therefore, intramuscular electromyogram is commonly used as a diagnostic tool in clinical practice.

Modern electromyogram analysis has been used for some decades. It is focused on signal processing and graphical representation of the signals [3] [4]. In the last decade, many applications were introduced. In 2005, Nihal implemented an artificial neural network to diagnose neuromuscular disorders [3]. His results showed 91.6 - 94.4% classification accuracy. In 2006, Subasi [4] introduced a wavelet coefficient method to classify the EMG signals. In 2010, Sabri [5] introduced a neuro-fuzzy system to classify EMG signals. Its performance showed 83.3 – 90% classification accuracy.

Analyzing nonlinear time series through recurrence quantification analysis has been investigated for many years [6] [7]. To test whether electromyogram is a nonlinear signal or just random noise, we analyze EMG signals of neuromuscular diseases using recurrence plot (see Figure 1). From all the results, we conclude that EMG obeys a certain nonlinear deterministic law and non-stationarity is significant within these signals. It is therefore possible to study and analyze these signals as a non-linear system using recurrence quantification analysis.

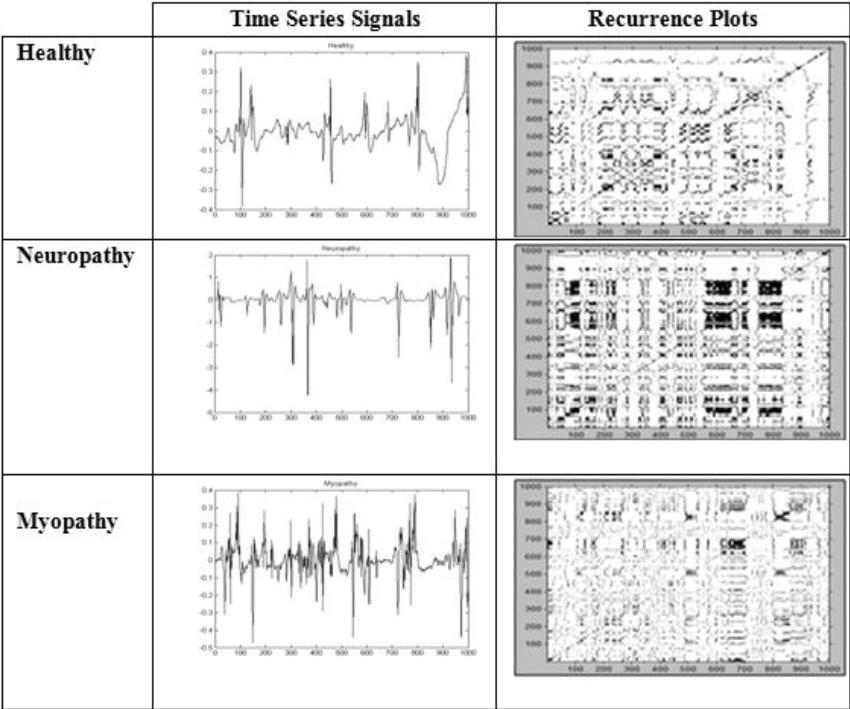


Fig. 1 Electromyogram signals of neuromuscular diseases

In this paper, we introduce a novel diagnosis and classification method for neuromuscular disorders; this method uses recurrence quantification analysis and a support vector machine. Our proposed method is evaluated using electromyogram signals corresponding to three different neuromuscular disorders: healthy, neuropathy, and myopathy. In order to extract their features, we apply recurrence quantification analysis as feature extraction. The classification of neuromuscular disorders is obtained from support vector machine learning. Furthermore, electromyogram signals of myopathy, neuropathy, and healthy subjects are used for analyzing the diagnostic performance of neuromuscular disorders.

2. Recurrence Quantification Analysis

The recurrence statistics, which is called recurrence quantification analysis (RQA), has been introduced for measuring quantitative information within recurrence plots [8]; subsequently it was extended with new measure of

complexity by Marwan [9] [10]. It is a method of nonlinear data analysis which quantifies the numbers and duration of recurrence of a dynamical system presented by its state space vector. An EMG recurrence plot, which includes the recurrence statistics, is a representation of the nonlinear EMG signal that provides rich information about EMG patterns. We focus on the following three features of the recurrence plot as they best describe the behaviour of the underlying EMG signals:

(a) *Recurrence rate (RR)* is the density of recurrence points in a recurrence plot, which is defined as [8]:

$$RR = \frac{1}{N^2} \sum_{i,j=1}^N R_{i,j} \quad (1)$$

where N is number of points on the phase space trajectory

(b) *Determinism (DET)* is the fraction of recurrence points forming diagonal lines, which is defined as [8]:

$$DET = \frac{\sum_{l=l_{\min}}^N IP(l)}{\sum_{i,j}^N R_{i,j}} \quad (2)$$

where N is the number of diagonal lines in the recurrence plot, and $P(l)$ is the histogram of the length l of the diagonal lines.

(c) *Laminarity (LAM)* is the percentage of recurrence points forming vertical lines, which is defined as [9] [10]:

$$LAM = \frac{\sum_{v=v_{\min}}^N vP(v)}{\sum_{v=1}^N vP(v)} \quad (3)$$

where N_v is the number of vertical lines in the recurrence plot, and $P(v)$ is the histogram of the lengths v of the vertical lines.

3. Proposed Method

We introduce the feature extraction based on recurrence quantification analysis in combination with the support vector machine classifier. The details of the proposed classification method are shown in Fig. 2. This approach allows us to extract the features of electromyogram signals from recurrence quantification analysis. Also we use these features to classify the type of neuromuscular disorders via support vector machines.

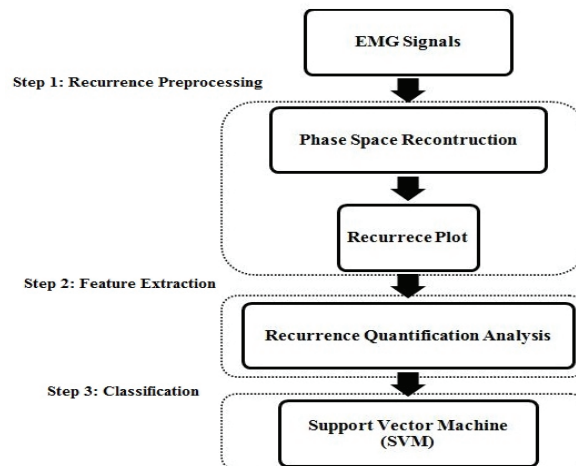


Fig. 2 The steps in the proposed method for classification of EMG signals

3.1. Recurrence Preprocessing (step 1)

In proposed method, recurrence preprocessing plays an important role to convert the electromyogram signal into a recurrence plot in order to extract their features using recurrence quantification analysis. The electromyogram is preprocessed by transforming it into phase space trajectories [11] and then creating the recurrence plot [6] [10]. Usually, a phase space does not have low enough dimensions to be visualized in three-dimensional space. Higher-dimensional phase space can only be visualized by projecting it into two- or three-dimensional sub-spaces. However, the recurrence plot enables us to investigate the m -dimensional phase space trajectory through a two dimensional representation of its recurrences. According to recurrence plots, we investigate the characteristics of electromyogram signals including their features and patterns. This preprocessing improves the classification accuracy of neuromuscular disorders.

3.2. Feature Extraction (step 2)

After transforming the EMG signals into recurrence plots in step 1, the three features (*Recurrence Rate (RR)*, *Determinism (DET)*, and *Laminarity (LAM)*) of the recurrence quantification analysis are extracted to form the input vector. These extracted features have been chosen by examining their ability to differentiate patterns of different neuromuscular disorders using the box plots for each feature in every class as shown in Fig. 3.

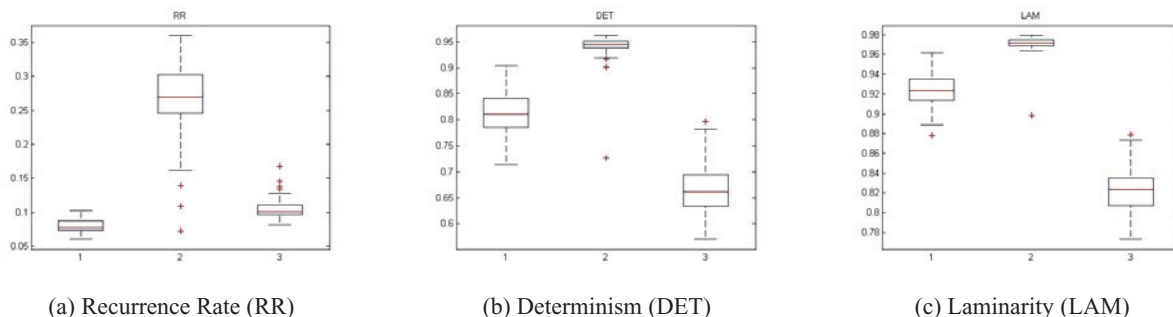


Fig. 3 The distribution of training data based on three classes of neuromuscular disorder

3.3. SVM Classifier (step 3)

Support vector machine plays an important role as classifier of electromyogram. It learns the relationship between features and the actual target from a set of representative training samples. Once the support vector machine learns the mapping between recurrence measurements and the actual target, it can classify neuromuscular disorders through feature extractions.

We create a support vector machine by employing a radial basis function (RBF) as a kernel function. In the proposed classification scheme, the data is fed to a separate recurrence preprocessing which provides the classification based on that individual data measurement. It provides a highly accurate and robust classification.

4. Experiments and Results

We conduct two sets of experiments to test the accuracy of the proposed method. The data from Set 1 experiments is used for training the support vector machine by using the extracted features from the recurrence quantification analysis. The data from Set 2 experiments is used to study the classification performance of the support vector machine at the same conditions that were used to train the support vector machine.

Data were collected with a Medelec Synergy N2 EMG Monitoring System. A 25mm concentric needle electrode was placed into the tibialis anterior muscle of each subject. The signals are recorded at 50 KHz and then downsampled to 4 KHz. During the recording process two analog filters are used: a 20 Hz high-pass filter and a 5K

Hz low-pass filter. Each of these signals belongs to one of three different classes: healthy (class 1), neuropathy (class 2), and myopathy (class3). The training data set (set 1) has 192 EMG signals (each signal is defined by 512 points) including 29 healthy, 88 neuropathy, and 75 myopathy; and the testing data set (set 2) has 100 EMG signals including 15 healthy, 50 neuropathy, and 35 myopathy. For each data set, we extract the three features described in Section 2 from the electromyogram.

We use cross-validation to find the best parameters for the support vector machines. The results confirm that the classification accuracy of the SVM with radial basis function kernel function is 98.28%. The classification efficiency which is defined as the percentage ratio of the number of electromyogram correctly classified to the total number of electromyogram observed for classification is shown in Table 1.

Class	Training set (Set 1)	Test set (Set 2)	Overall
Healthy	100.00%	93.33%	97.72%
Neuropathy	98.86%	94.00%	97.10%
Myopathy	100.00%	100.00%	100.00%
Overall	99.47%	96.00%	98.28%

Table 1. The classification accuracy of neuromuscular disorders in our methodology

5. Discussion

Figure 4 show the position of the neuromuscular phase in the feature space (DET , LAM , RR). As one can notice, the clusters relative to all classes are separated, and the healthy class is positioned in the central part of the diagram. It is worth noticing that, from the clinical point of view, neuropathy and myopathy are separated.

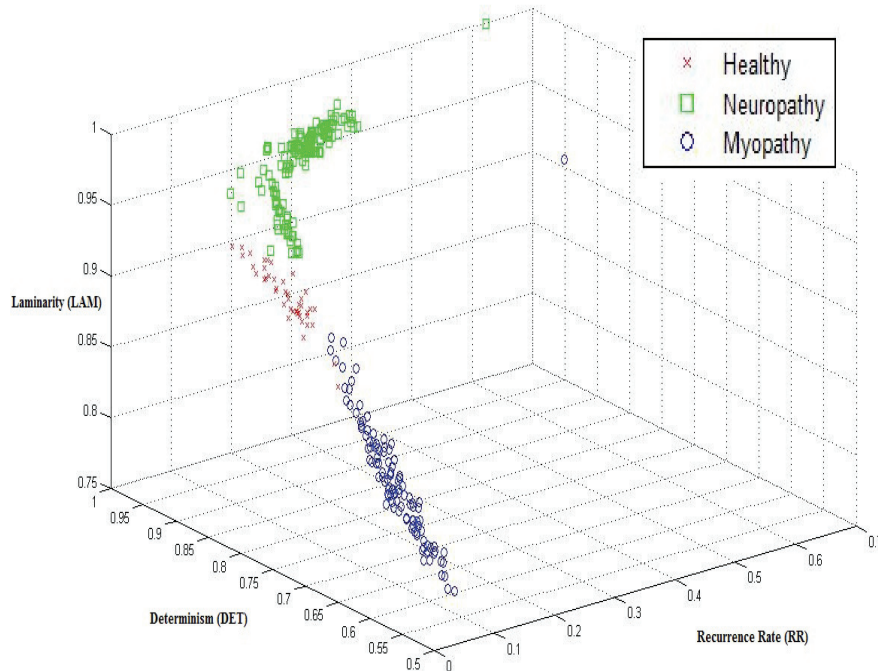


Fig. 4 Position of the neuromuscular phases in the (DET , LAM , RR) feature space

The results show that the proposed method offers very high classification accuracy. It should be noted that our data may contain healthy or unhealthy acoustic signals but altogether are completely classified by our framework. Consequently, the proposed method performs the classification task ideal even though the data might contain turbulence noise.

While other approaches [3] [4] [5] have produced classification accuracy of 86 to 94.4%, our method show better classification accuracy. The comparison of accuracy performance of the classification of neuromuscular disorders in testing data set is shown in Fig. 5.

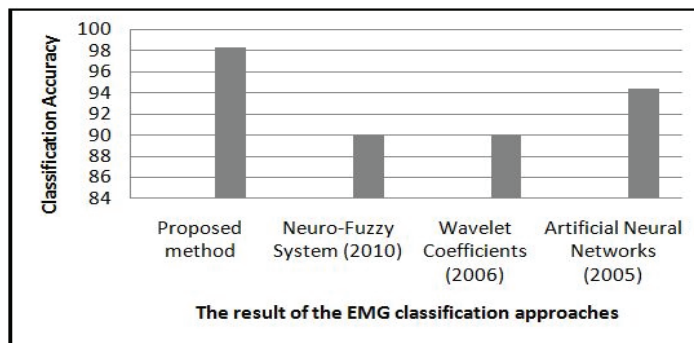


Fig. 5 Comparison of accuracy performance of the classification of neuromuscular disorders

6. Conclusion

Electromyography plays an important role in clinical neurological diagnosis; it can confirm or dismiss clinical diagnoses, indicate the location and type of an abnormality or expose disorders that are clinically uncertain. The classification of neuromuscular disorders is an essential for correct diagnosis. Moreover, many methods of time series analysis do not rely on the characteristics of electromyogram because of their complexity, nonlinearity, and non-stationarity. In this paper, a novel framework of diagnostic classification of neuromuscular disorders is proposed.

The electromyogram signals are transformed into recurrence plots and a set of statistical features are calculated using recurrence quantification analysis. Our results show that specified features play an important role as feature extraction in our method. We simulate the classification of neuromuscular disorders using these features in support vector machine. Support vector machine employing radial basis function is found to be effective for diagnosis and classification of neuromuscular disorders. The results show that our method gives 98.28% classification accuracy.

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